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Satellite and Diagnostic Model Estimates of Precipitation Susceptibility in Low-level, Marine Stratocumulus

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1 Satellite estimates of precipitation susceptibility in 2 low-level, marine stratiform clouds

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Abstract. Quantifying the sensitivity of warm rain to aerosols is important for constraining climate model estimates of aerosol indirect effects. In this study, the precipitation sensitivity to cloud droplet number concentration (N_d) in satellite retrievals is quantified by applying the precipitation susceptibility metric to a combined CloudSat/MODIS dataset of stratus and stratocumulus that cover the tropical and subtropical Pacific Ocean and Gulf of Mexico. Consistent with previous observational studies of marine stratocumulus, precipitation susceptibility decreases with increasing liquid water path (LWP), and the susceptibility of the mean precipitation rate R is nearly equal to the sum of the susceptibilities of precipitation intensity and of probability of precipitation. Consistent with previous modeling studies, the satellite retrievals reveal that precipitation susceptibility varies not only with LWP but also with N_d . Puzzlingly, negative values of precipitation susceptibility are, however, found at low LWP and high N_d . There is marked regional variation in precipitation susceptibility values that cannot simply be explained by regional variations in LWP and N_d . This suggests other controls on precipitation apart from LWP and N_d and that precipitation susceptibility will need to be quantified and understood at the regional scale when relating to its role in controlling possible aerosol-induced cloud lifetime effects.

1. Introduction

General circulation models and weather forecast models are increasingly incorporating processes by which aerosols can affect cloud properties. The effects of aerosols are represented in various ways, including impacts on cloud radiative properties and cloud microphysical processes. However, comparisons of the radiative forcing of aerosols between satellite retrieval-based estimates and global models show large disagreement, with models predicting a larger cooling effect of aerosols [Quaas *et al.*, 2009; Boucher *et al.*, 2013]. Part of the discrepancy might exist because global models inaccurately represent how precipitation depends on the cloud droplet number concentration [Wang *et al.*, 2012].

Attempts to constrain the integrated effect of aerosols on the cloud radiative properties from observations have been confounded by covariances between meteorology and aerosol conditions [Mauger and Norris, 2007; George and Wood, 2010; Gryspeerd *et al.*, 2014]. Although efforts have been made to use conditional sampling of meteorology to isolate only the aerosol effect, concerns still exist [Gryspeerd *et al.*, 2014]. Another approach to constrain the effect of aerosols on clouds is to examine the intermediate processes that connect aerosol changes to cloud changes [Sorooshian *et al.*, 2010].

In the cloud lifetime hypothesis proposed by Albrecht [1989], whereby increases in aerosol concentrations lead to increases in cloud lifetime, a crucial part of the argument hangs on the suppression of precipitation due to increases in aerosol concentrations. Previous observational studies have clearly demonstrated that precipitation from low-lying liquid clouds is suppressed by increases in aerosol and cloud droplet number concentration [Pawlowaska and Brenguier, 2003; Comstock *et al.*, 2004; Sorooshian *et al.*, 2009;

43 *Teraï et al.*, 2012; *Mann et al.*, 2014]. Earlier studies applied a multi-linear regression to
 44 all available data to obtain a single value to quantify the suppression of precipitation due
 45 to increases in aerosol concentrations [*Pawlowska and Brenguier*, 2003; *Comstock et al.*,
 46 2004; *vanZanten et al.*, 2005], whereas the availability of more data and unique observa-
 47 tional strategies have allowed an examination of how the suppression varies with cloud
 48 thickness [*Sorooshian et al.*, 2009; *Teraï et al.*, 2012; *Mann et al.*, 2014]. The underlying
 49 goal has been to determine whether the necessary and sufficient controls that determine
 50 the suppression can be identified in order to understand differences amongst various ob-
 51 servational estimates. Our study attempts to constrain the strength of this precipitation
 52 suppression using the precipitation susceptibility metric of *Feingold and Siebert* [2009].
 53 In addition, we attempt to understand how susceptibility varies with cloud liquid water
 54 path (LWP), because studies currently disagree on the cloud LWP dependence [*Sorooshian*
 55 *et al.*, 2009; *Jiang et al.*, 2010; *Teraï et al.*, 2012; *Mann et al.*, 2014]. The precipitation
 56 susceptibility metric S_R quantifies the fractional decrease of precipitation rate (R) due to
 57 a fractional increase in cloud droplet number concentration (N_d) [*Feingold and Siebert*,
 58 2009]. If we define R to be the mean precipitation rate averaged over an area, time period,
 59 or bin, R can be decomposed into the fraction f of cloud observations that are precipitat-
 60 ing (analogous to the probability of precipitation - POP - of *Wang et al.* [2012]) and the
 61 precipitation intensity I (the precipitation rate of those clouds that are precipitating). In
 62 other words,

$$R = fI. \quad (1)$$

In the susceptibility metric S_R , f and I can be replaced for R such that the susceptibility

can take the functional form

$$S_x = - \left(\frac{\partial \ln x}{\partial \ln N_d} \right)_{macro}, \quad (2)$$

where x represents R , f (or POP), or I [Terai et al., 2012] and *macro* indicates that cloud macrophysical properties are constrained to reduce the effect of covariances on quantifying the precipitation suppression due to N_d . Studies so far have largely only accounted for the LWP control on precipitation, whereas other controls on precipitation may exist that may act independent of LWP (e.g., turbulence - Baker [1993], giant cloud condensation nuclei - Feingold et al. [1999]).

Initial studies examining the precipitation susceptibility in parcel models, satellite retrievals, and large eddy simulations of cumulus cloud fields examined S_I and noted that S_I initially increases with increasing cloud LWP, reaches a peak value, and then decreases at higher LWP [Feingold and Siebert, 2009; Sorooshian et al., 2009; Jiang et al., 2010]. At the same time, steady-state simple models [Wood et al., 2009], aircraft observations [Terai et al., 2012], and ground-based cloud radar retrievals [Mann et al., 2014] have found that susceptibility monotonically decreases with increasing cloud LWP. In these studies, Wood et al. [2009] quantified S_R , whereas Terai et al. [2012] and Mann et al. [2014] both examined S_R and S_f , where the decrease with LWP was general only in the behavior of S_f . Much of the difference in the behavior of susceptibility between the two sets of studies possibly lies in whether R , f , or I is used to calculate the susceptibility. When the susceptibilities of the three variables R , f , and I were examined in aircraft measurements, Terai et al. [2012] found that $S_R \approx S_f + S_I$. Because R is the product of f and I (Eq. 1)

and the susceptibility takes the derivative in log-space (Eq. 2), when the non-linear term capturing the covariance between f and I is small, the S_f and S_I are additive (see *Teraï et al.* [2012]). Because S_f and S_{POP} are the same if we aggregate both temporal and spatial variations to calculate the susceptibility, we will henceforth refer to S_{POP} to stay consistent with previous studies [*Wang et al.*, 2012; *Mann et al.*, 2014]. Susceptibilities of all three aspects of the precipitation will be examined in this study.

The multi-model study of *Wang et al.* [2012] shows the possibility that the precipitation susceptibility can be used to constrain the strength of the cloud lifetime effect in climate models. The magnitude of the precipitation susceptibility metric (S_{POP}) and the sensitivity of LWP to aerosol concentration ($dLWP/dN$) in climate models were examined by *Wang et al.* [2012] and found to correlate, such that models with strong precipitation susceptibilities also exhibited large increases in LWP with N . Although the cloud lifetime effect as originally proposed specifically pointed to the increase in cloud fraction due to the suppression of precipitation [*Albrecht*, 1989], we use the term more broadly to include the increase in cloud LWP due to the suppression of precipitation. Based on the high S_{POP} calculated in the default version of the Community Atmosphere Model ver.5 (CAM5) compared to the S_{POP} calculated from satellite retrievals, the authors argued that the cloud lifetime effect within CAM is likely overestimated [*Wang et al.*, 2012].

In this study, we examine a set of satellite retrievals obtained from the CloudSat and MODIS instruments, focusing on marine stratiform clouds over the tropical and subtropical Pacific to derive the precipitation susceptibility. We specifically address the extent to which susceptibility values and behaviors across different platforms and observations can be reconciled and whether underlying commonalities exist. Section 2 introduces the

CloudSat and MODIS combined dataset and various methods used to calculate the precipitation susceptibility. Section 3 presents the susceptibilities from the CloudSat and MODIS retrievals and explores the uncertainties and sensitivity of the susceptibilities to N_d and regional choices. Finally in Section 4, we present a discussion and our conclusions.

2. Methods

2.1. CloudSat and MODIS combined dataset

The satellite retrievals used in this analysis are of warm cloud properties analyzed by *Kubar et al.* [2009] (K09, hereafter) and *Wood et al.* [2009]. They pertain to twelve months of CloudSat and MODIS retrievals of cloud LWP, effective cloud droplet number concentration (N_{eff}), and radar reflectivity (September 2006-February 2007 and September 2007-February 2008) between 30°S and 30°N and between 100°E and 70°W, mostly consisting of clouds over the tropical and subtropical Pacific Ocean and Gulf of Mexico. The MAC06S0 version of the MODIS/Aqua level-2-cloud subset and the CloudSat 2B-GEOPROF data are used, and K09 found that the relationships between precipitation and cloud properties are insensitive to the months used. Given the strict criteria to screen for stratiform clouds whose microphysical retrievals are less affected by cloud edges and heterogeneities [*Zhang and Platnick*, 2011], the cloud types analyzed here are low-level, marine, stratiform clouds with cloud top temperatures warmer than 273 K. Of all MODIS-detected clouds in the region and during the time period, 21 % of them are included in this analysis (K09). Others are not used for the following reasons. Cloud liquid water path (LWP) is retrieved using the cloud optical thickness (τ) and effective radius (r_{eff}) (K09). N_{eff} , which represents an estimate of N_d based on satellite retrievals, is estimated assuming the clouds are adiabatic using the method of *Bennartz* [2007] (K09). Because

accurate retrievals of N_{eff} cannot be made around broken clouds, data are included only if the MODIS retrievals recorded a cloud fraction of 100% in a box with sides of 5 km along the satellite track and 15 km across the satellite track.

The column maximum reflectivity (Z_{max}) is used to infer the presence of drizzle and to estimate precipitation rate (R). A reflectivity threshold of -15 dBZ is used to distinguish precipitating from non-precipitating clouds [Comstock *et al.*, 2004; Kubar *et al.*, 2009; Terai *et al.*, 2012], and a $Z - R$ relationship from Comstock *et al.* [2004], based on liquid stratocumulus clouds, is used to estimate R from Z_{max} . The $Z - R$ relationship does not take into account the attenuation of Z_{max} by liquid water in the cloud. Given that the clouds examined here have LWPs typically below 500 g m^{-2} , the effect of attenuation on the susceptibility estimates are likely small, and a sensitivity test assuming an attenuation of approximately 8 dBZ per 1000 g m^{-2} of LWP [Hogan *et al.*, 2005] shows that it does not affect our susceptibility values.

Assuming that the observed clouds are adiabatic, particularly affects the calculation of N_{eff} in the equation

$$N_{\text{eff}} = \sqrt{2} B^2 \Gamma^{1/2} \frac{\text{LWP}^{1/2}}{r_{\text{eff}}^3}, \quad (3)$$

where $B = (3/4\pi\rho_w)^{1/3} = 0.0620$ and Γ is the rate of increase of liquid water concentration with respect to height (K09). Γ is derived from $\Gamma = f_{ad}\Gamma_{ad}$, where Γ_{ad} is the thermodynamically determined increase of liquid water concentration for a parcel ascending adiabatically and only a function of temperature and pressure, both of which are obtained from European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis profiles of temperature and pressure. In this study, f_{ad} is assumed to equal

one. With thicker clouds, precipitation and evaporative mixing reduce the ratio Γ/Γ_{ad} [Zuidema et al., 2005; Rauber et al., 2007]. Because Γ is not directly observable from space, we estimate the sensitivity of assuming that $f_{ad} = 1$ by also calculating the susceptibility when we use the approximation that $f_{ad} = z_0/(z_0 + z)$, where z_0 , the cloud base height is set to 705 m, which is the mean lifting condensation level found across the regions in the ECMWF profiles, and z is the height above cloud base. In relating N_{eff} to the cloud droplet number concentration N_d , we also assume that r_{eff} is equal to the mean volume radius. We explore their potential effect on our results in Sect. 3.1.

The analysis is constrained to warm, marine stratiform clouds with optical depth greater than 3 (K09) due to MODIS retrieval uncertainties when clouds are thin or broken [Zhang and Platnick, 2011]. Thus, this paper does not consider the response of cumulus precipitation to aerosol concentrations. Furthermore, we exclude thin clouds in the analysis and do not consider the response of mid-latitude stratocumulus clouds, a large proportion of which have been found to precipitate as well [Leon et al., 2008; Muehlbauer et al., 2014]. However, unlike previous precipitation susceptibility studies of marine stratocumulus [Terai et al., 2012; Mann et al., 2014], we examine clouds over a wide geographic area with different ranges of aerosol and meteorological conditions. Because retrievals of LWP and N_{eff} are only possible during the daytime, we restrict our analysis to clouds and precipitation observed $\sim 13:30$ local, while acknowledging that diurnal differences in precipitation exist and that 13:30 is near the diurnal minimum of marine stratocumulus cloud cover and precipitation rate [Leon et al., 2008; Burleyson et al., 2013].

2.2. Susceptibility metric

The parameters that go into calculating the susceptibility can vary from study to study. For example, instead of N_d , the aerosol concentration (N), which is unavailable from space, or the aerosol index (AI) may be used [Nakajima *et al.*, 2001; Sorooshian *et al.*, 2010]. In this study, we examine the susceptibility due to variations in N_{eff} . Susceptibilities are typically calculated in bins of cloud LWP to control for the influence of LWP on precipitation. Different methods exist to calculate the susceptibility in each LWP bin, whether using linear regression in log-log space and using the slope to calculate susceptibility [Sorooshian *et al.*, 2010] or binning the data by N_d (or N), calculating the bin-mean N_d and R to calculate the susceptibility [Terai *et al.*, 2012; Wang *et al.*, 2012; Mann *et al.*, 2014]. Most of the susceptibility estimates in this study are made by binning the LWP-binned data further into bins of N_d and taking the linear regression of the bin-mean N_d and R , but the tercile log-difference method of Terai *et al.* [2012], in which the log-difference in the means of the bottom and top terciles of N_d are used to calculate the susceptibility, is also used to show that they give nearly identical susceptibility values.

3. Results: Satellite susceptibility

3.1. Basin-wide susceptibility as a function of LWP

Before calculating the susceptibility, the satellite data are first binned according to LWP and N_{eff} values. We divide the approximately 400000 total CloudSat profiles into a hundred approximately equally sized bins of LWP and N_{eff} bins, leaving each of the hundred [LWP, N_{eff}] bins with about 4000 profiles, ranging from 1200 to 5500 (middle 90th percentile of 3090-4660). In each [LWP, N_{eff}] bin, we calculate the bin-mean precipitation metrics R , POP , and I , as well as N_{eff} . The susceptibility is then calculated

by taking the linear regression in log-space across those ten means. We use a threshold of -15 dBZ, as in previous studies [Comstock *et al.*, 2004; Bretherton *et al.*, 2010; Terai *et al.*, 2012], to discriminate between drizzling and non-drizzling clouds. This corresponds to a precipitation rate threshold of approximately 0.14 mm d^{-1} [Comstock *et al.*, 2004]. We find that S_R equals approximately 0.6 at low LWP and slightly decreases to 0.5 with increasing LWP for clouds with a N_{eff} range of 20 to 200 cm^{-3} (Fig. 1a). This is in contrast with other observational studies of stratocumulus, which found a 40 % to 45 % decrease in susceptibility with increasing cloud LWP [Terai *et al.*, 2012; Mann *et al.*, 2014]. The difference between the previous observational estimates, obtained in limited area studies, and the Pacific basin-wide values in (Fig. 1a) raises the question whether examining the susceptibilities at smaller regional scales will lead to a better agreement. Note the large error bars for the susceptibility values at low LWP. These error bars are the 95 % confidence intervals in the slopes calculated by linear regression. Feingold *et al.* [2013] found that in their model analysis of a large number of parcel ensembles based on large-eddy simulations of previously observed precipitating stratocumulus and stratus clouds, susceptibility is not only a function of LWP, but also of the cloud droplet number concentration N_d , suggesting that the $\log(R)$ vs. $\log(N_d)$ relationship is not linear across all N_d , potentially leading to the wide confidence intervals at low LWP. In particular, they found that in stratocumulus and stratus clouds, the susceptibility is higher in clouds with low N_d . In Sect. 3.3 we explore how susceptibility varies with N_{eff} .

Because R is the product of POP and I in each bin, S_R can be approximated as the sum of S_{POP} and S_I [Terai *et al.*, 2012]. In other words, as in Terai *et al.* [2012], despite the wide confidence intervals at low LWP, $S_R \approx S_{POP} + S_I$, which indicates that the

non-linear covariance term between POP and I is small. The implications are that we can understand the behavior of S_R in terms of the magnitude and behavior of S_{POP} and S_I . We find that S_{POP} decreases with increasing LWP (Fig. 1b), whereas S_I increases with increasing LWP. The decrease of S_{POP} with increasing LWP agrees with previous observational studies [Terai et al., 2012; Wang et al., 2012; Mann et al., 2014], but the increase in S_I does not. Sorooshian et al. [2009] and Feingold et al. [2013] found that S_I increases with LWP in the LWP range examined in this study, from a value of 0.55 to 0.65 in Sorooshian et al. [2009] and from 0.6 to 0.85 in Feingold et al. [2013], but Terai et al. [2012] found that S_I increased negligibly, with a constant value of 0.5. The qualitative behavior of S_I here is not inconsistent with that of Sorooshian et al. [2009] and Feingold et al. [2013], but the values of S_I vary substantially.

The negative S_I values at low LWP in Fig. 1 are especially difficult to explain in the context of our current understanding of how N_d affect warm rain processes. What Fig. 1 implies is that at $LWP < 150 \text{ g m}^{-2}$, increasing N_d decreases the frequency of precipitation (positive S_{POP}) but increases the intensity (negative S_I). To test whether this is an artifact of the method by which we calculated susceptibility, we use the tercile log-differencing (TLD) method used by Terai et al. [2012] to calculate the susceptibility in Fig. 1d and still find similar behaviors for S_R , S_{POP} , and S_I . We also examined whether covariances existed between N_{eff} and other cloud properties that may explain the negative S_I , such as cloud top height and r_{eff} , but found none.

Various assumptions go into deriving the susceptibility estimates. Now we discuss the potential impacts of those assumptions and uncertainties in the retrievals on the susceptibility estimates. To derive a precipitation rate from the reflectivity, we have used the

$Z - R$ relationship from *Comstock et al.* [2004]. Others exist, such as the relationship from *vanZanten et al.* [2005], which predicts a weaker dependence of R on Z . The choice of $Z - R$ has a small effect on S_R (< 0.06), because it only affects the estimates of I , not of POP, and the effect on S_I is to reduce its magnitude by approximately 15 %. Related to the precipitation, we also assume that precipitation scavenging has a negligible effect when quantifying the effect of N_{eff} on R , rather than the effect of R on N_{eff} . With typical precipitation rates of 2 mm d^{-1} and a cloud droplet concentration of 50 cm^{-3} , the parameterization of cloud drop scavenging rate from *Wood* [2006] gives a scavenging rate of $3 \text{ cm}^{-3} \text{ hr}^{-1}$. Given an approximate lifetime of a drizzle cell of two hours [*Comstock et al.*, 2005], the effect would be to reduce N_d by approximately 10 % over the lifetime of the cloud. We expect to find the effect to be larger in heavier precipitating clouds, given that the fractional reduction from coalescence scavenging in N_d scales with R in the parameterization [*Wood*, 2006]. Since R is generally higher in clouds with low N_d , the potential effect of the precipitation scavenging would likely be a low bias of the susceptibility values on the order of 0.1. This potential bias is on par with the statistical uncertainty represented by the sampling confidence intervals.

Another assumption that is made in relating N_{eff} to N_d is that the ratio between r_{eff} and the mean volume radius is one. We assume the ratio of one, because we are unable to retrieve the ratio without knowledge of the drop size distribution. Past measurements show that this can lead to underestimating the true N_d by up to 20 % in more polluted clouds [*Brenguier et al.*, 2000]. The maximum potential effect on the susceptibility will be a positive bias in the susceptibility by 0.2, if the ratio changes systematically with N_d .

Finally the assumption of an adiabatic cloud has possible implications. As noted by K09, if a parameterization found to approximate the adiabaticity of clouds is used on the MODIS retrievals used here, the subadiabatic N_{eff} ranges from 51 % of the adiabatic value in the thickest of clouds over the Asian Coast to 68 % of the adiabatic values in the thinnest of clouds over the far southeast Pacific. Therefore, these values may have a substantial effect on the susceptibility values, especially if covariances exist between the thickness of the cloud and N_{eff} . When we compare the S_R using the subadiabatic N_{eff} values, we find that the general effect of using subadiabatic N_{eff} is to shift all the N_{eff} values in a LWP bin to lower values but not to largely alter the slope by which the susceptibilities are calculated. Susceptibility values are larger, generally on order of 0.1, when the subadiabatic N_{eff} is used. However, the general results of the study remain unchanged.

3.2. 0 dBZ threshold

Previous studies have examined the susceptibility using a different reflectivity threshold than the -15 dBZ that we have used [Sorooshian *et al.*, 2009; Wang *et al.*, 2012; Mann *et al.*, 2014]. We examine how changing the threshold changes our results. The 0 dBZ threshold is a more meaningful threshold if one is interested in surface precipitation, given that cloud base precipitation with -15 dBZ rarely reaches the surface due to subcloud evaporation [Comstock *et al.*, 2004]. In Fig. 2, we plot the susceptibility as a function of LWP using a minimum threshold of 0 dBZ.

Increasing the minimum threshold decreases S_I to near zero values across all LWP, and S_R values mostly correspond to S_{POP} values. Based on the $Z - R$ relationship of Comstock *et al.* [2004] a 0 dBZ threshold corresponds to approximately 2 mm d^{-1} . The

implication of the near zero S_I values is that heavy drizzle intensity is not susceptible to aerosols. S_{POP} , and hence also S_R , decreases for clouds with $LWP < 150 \text{ g m}^{-2}$, while the S_{POP} values at higher LWP remain little changed.

At first glance, S_R and S_{POP} calculated using linear regression and the TLD method appear to disagree (Fig. 2a vs. Fig. 2b). The susceptibilities in the first four LWP bins are not calculated using the TLD method because less than 10% of the data points in the upper tercile of N are found to be precipitating with the new threshold. If we only compare those bins where the two methods report values, the values agree within uncertainty. Likewise, if we only compare the susceptibilities using the -15 dBZ threshold and 0 dBZ threshold where more than 10% of the data points in the upper tercile of N are found to be above the 0 dBZ threshold ($LWP > 150 \text{ g m}^{-2}$), we note that the S_R values are similar even though the S_{POP} and S_I values disagree (Fig. 2a vs. Fig. 2b). This is mostly in agreement with *Mann et al.* [2014] who examined the sensitivity of results to changing thresholds and found little change in S_R , although *Teraï et al.* [2012] found that susceptibilities can be sensitive to choice of threshold. The susceptibilities calculated by *Sorooshian et al.* [2009] and *Gettelman et al.* [2013] correspond to S_I of this study, and the near-zero S_I values for $LWP < 300 \text{ g m}^{-2}$ in Fig. 2 do not agree with either study's estimates. Given that S_I is sensitive to the thresholds used, it is perhaps not surprising that the values disagree. This shows the difficulties of comparing S_I across different observational platforms. From the analysis here and from *Mann et al.* [2014], S_R appears to be a metric that is more robust to threshold choice.

3.3. Susceptibility as a function of LWP and N_{eff}

As we mentioned in Sect. 3.1, the $\log R$ vs. $\log N_{\text{eff}}$ relationship, especially at low LWP, is not linear (see Fig. 3a). As a result, we see particularly large error bars in the susceptibility values at low LWP in Fig. 1a. The large range of LWP and N_{eff} retrievals in the combined MODIS/CloudSat dataset allows us to examine the variation in susceptibility as a function of N_{eff} , in addition to LWP. We calculate the susceptibility at each LWP and N_{eff} bin by using three consecutive N_{eff} bins, rather than the full range of N_{eff} , to calculate the susceptibility. We might expect large uncertainties in the susceptibilities that we calculate from the slopes calculated from a linear regression of only three points, but this method allows us to better see whether there are systematic changes in susceptibility with N_{eff} . In previous sections we have found that S_I is negative for clouds with low LWP (Fig. 1c). We can examine this issues in more detail by considering how susceptibility varies with N_{eff} .

S_R (Fig. 4a), S_{POP} (Fig. 4b), and S_I (Fig. 4c) are plotted as a function of LWP and N_{eff} from the satellite data. We find that S_R is highest at low LWP and low N_{eff} and decreases with increasing LWP and N_{eff} , such that susceptibilities are zero or negative in clouds that are thin and polluted (low-LWP/high- N_{eff}) and thick and clean (high-LWP/low- N_{eff}). This pattern largely mimics that of S_{POP} . By comparing Fig. 4b and Fig. 4c, we can see that S_I is largest at slightly higher LWP and lower N_{eff} compared to where S_{POP} maximizes.

As shown in Fig. 4c, negative values of S_I in Fig. 1b largely occur in low-LWP/high- N_{eff} clouds. As stated previously, negative S_I is difficult to conceptually understand. One may hypothesize that the proximity of mean I in low LWP clouds to the minimum threshold of -15 dBZ, shown as a dashed line in Fig. 3b, leads to statistical uncertainty

in I and to a spurious increase of I with increasing N_{eff} . However, given that each bin has approximate 4000 data points and probability of precipitation is at least 2%, there are at least 80 profiles that contribute to the mean I . Furthermore, the increase of I across four of the lowest LWP bins in Fig. 3b suggests a structural feature in the data, where an unconsidered environmental factor that increases I positively correlates with N_{eff} . For example, *Baker* [1993] found that precipitation formation was enhanced by stronger turbulence. If in-cloud turbulence is enhanced in more polluted clouds, this may potentially lead to increased precipitation. Although we may speculate about the sources of this odd behavior, we do not have an adequate and testable explanation. Further investigation is necessary to understand what artifacts or mechanisms may lead to the negative values of S_I .

3.4. Regional differences

We acknowledge that N_{eff} and LWP are not the only controls on precipitation rate [*Baker*, 1993; *Feingold et al.*, 1999]. *L'Ecuyer et al.* [2009] found that if they further binned their data by the lower tropospheric stability (LTS), in addition to LWP and aerosol index (AI), the proxy they used for aerosol concentration, the probability of precipitation for clouds with $\text{LWP} > 500 \text{ g m}^{-2}$ was greater in stable conditions, regardless of high or low aerosol conditions. We have tried to account for stability regimes by exclusively analyzing marine stratiform clouds, which occur most frequently under stable lower tropospheres [*Klein and Hartmann*, 1993], but our susceptibility results may still be affected by mixing different LTS regimes. Therefore, we examine the susceptibility metric in different regions of the tropical/subtropical Pacific and Gulf of Mexico to determine whether the value and behavior of the susceptibility varies by region. This will also allow us to see whether the

negative S_I values at low LWP are found across all regions, or whether it is a signal that grows out of including a particular region in the basin-wide analysis.

In Fig. 5, we examine S_R , S_{POP} , and S_I in seven regions, which largely correspond to regions identified by K09. We have not examined the ITCZ and SPCZ, where deep convective clouds dominate. The far southeast Pacific area is modified from that defined by K09 to encompass the area sampled during VOCALS-REx [Teraï *et al.*, 2012; Mechoso *et al.*, 2014]. These seven regions encompass different aerosol and meteorological regimes. For example, compared to the other regions, the Asian coast has a much higher mean N_{eff} due to continental influences and also a higher LWP, compared to the remote SEP (K09). Similar to the susceptibility that we estimate based on all of the data, the susceptibilities here are estimated from binning the data in each region by LWP and N_{eff} and then taking linear regression of the binned data. Instead of the 100 total bins of [LWP, N_{eff}] used to calculate the susceptibility in the total data, the data in each region are binned into 25 total bins of [LWP, N_{eff}] such that the same number of profiles exists in each bin.

We summarize the regional-mean susceptibility values found across the various regions in Table 1. Whereas the global mean S_R value is approximately 0.6, the regional values range from 0.5 to 1.6. The highest S_R values are found over the VOCALS southeast Pacific (SEP) region and far northeast Pacific (NEP) region. These two regions are also where S_{POP} maximizes. Comparing the susceptibility values with the region-mean LWP and N_{eff} values, we note that the highest S_{POP} values tend to occur where the region-mean LWP are lowest, while the lowest S_{POP} values occur where LWP are highest. This is consistent with the decrease in S_{POP} with increasing LWP in Fig. 1. The S_I values do not have as strong a correspondence with region-mean LWP values, although the highest

regional-mean S_I values are found in regions where LWP is higher. We may then ask whether we may use the regional distribution of LWP and N_{eff} and the susceptibility values from Fig. 4 to accurately estimate the regional mean susceptibility values. These derived estimates are reported in brackets next to the regional mean susceptibilities in Table 1. Contrary to expectations, we find that knowing the regional LWP and N_{eff} distributions and the basin-wide behavior of susceptibilities as a function of LWP and N_{eff} cannot help us predict the regional susceptibility values.

From regional-mean values, we shift the focus to the behaviors of S_R , S_{POP} , and S_I across different regions. We find a wide variety of behaviors, which highlights how susceptibilities based on measurements made in one region will not necessarily agree with those from a different region. At the same time, however, consistent behaviors do appear. For example, S_{POP} across all regions decreases with increasing LWP. In addition, it appears that S_I increases with increasing LWP. Whether the increase is large and at what LWP that increase occurs varies by region. Furthermore, at low LWP, S_I is statistically indistinguishable from zero. Therefore, the negative S_I at low LWP is not a general feature of the satellite data. S_R has the most diversity across the regions, and is largely determined by the addition of S_I and S_{POP} behaviors, as in the Gulf of Mexico, where the increase in S_I is larger than the decrease in S_{POP} at low LWP, leading to an increase in S_R with LWP. We are therefore left with strong confidence in the general decrease of S_{POP} with increasing LWP, but we find that the behavior and value of S_R is more variable across regions and dependent on the behavior and value of S_I .

We expect the susceptibilities calculated over the VOCALS southeast Pacific region, just off the coast of South America, to agree with susceptibilities calculated by *Tera*

392 *et al.* [2012]. Because the geographic regions over which they are calculated are the same,
 393 this provides a rough comparison of what different observational platforms can have on
 394 the susceptibility values. First, S_R values from Fig. 9 of *Teraï et al.* [2012] agree with the
 395 values found in the southeast Pacific VOCALS region in Fig. 5. The sharp decrease in
 396 S_{POP} with increasing LWP is also observed in both results. Indeed, the susceptibilities
 397 found over the southeast Pacific VOCALS region agrees better with the results of *Teraï*
 398 *et al.* [2012] than do the susceptibilities in Fig. 1 that were estimated using all of the
 399 available data. However, the increase in S_I with increasing LWP, found in Fig. 5, is not
 400 found in the results of *Teraï et al.* [2012]. In particular, although the S_I values at LWP
 401 $\sim 200 \text{ g m}^{-2}$ agree between the two estimates, at $\text{LWP} < 100 \text{ g m}^{-2}$, the satellite data
 402 here suggest an $S_I \sim 0$, whereas the results of *Teraï et al.* [2012] suggest a value of 0.5.
 403 Although not shown in *Teraï et al.* [2012], we should note that S_I slightly increases (0.5
 404 to 0.7) with LWP in the range of LWP that they examined. Part of this discrepancy
 405 may be due to sampling differences between the satellite and aircraft radar retrievals.
 406 For example, the footprint of the CloudSat profiles is approximately 1.7 km by 1.3 km
 407 in the horizontal, while they are approximately 100 m in the aircraft data. *Teraï et al.*
 408 [2012] found that the averaging length can lead to differences in susceptibility of up to
 409 0.5, although the change in susceptibility with averaging length was not monotonic. Most
 410 of the observations from *Teraï et al.* [2012] were also obtained during late-night/early-
 411 morning flights, whereas the satellite observations are approximately from 13:30 local
 412 time. In addition, in this analysis we examine the susceptibility to changes to N_d whereas
 413 *Teraï et al.* [2012] examined the susceptibility to changes in accumulation-mode aerosol
 414 concentrations. Comparisons between the satellite and aircraft of radar reflectivities as

functions of LWP and N_d will be necessary to better understand why this discrepancy exists.

4. Discussion and conclusions

In this study we examine the precipitation susceptibility metric in marine stratiform clouds over the tropical and subtropical Pacific Ocean and Gulf of Mexico. The combined MODIS/CloudSat dataset gives us the opportunity to quantify the susceptibility as a function of cloud droplet number concentration and to examine how it varies by region, in order to determine whether any underlying features of the sensitivity of precipitation to aerosols can be generally understood.

Following on previous studies [*Sorooshian et al.*, 2009; *Jiang et al.*, 2010; *Teraï et al.*, 2012; *Wang et al.*, 2012; *Mann et al.*, 2014], we first calculate the susceptibility as a function of LWP, using all of the available data. Large uncertainties exist in the susceptibility values. Despite the large uncertainty values, we find that S_R can still be represented as a sum of S_I and S_{POP} . Whereas S_I and S_{POP} are quite sensitive to the choice of precipitation threshold, S_R is less sensitive, because S_{POP} increases and S_I decreases, essentially compensating each other, when the threshold is increased.

The wide range of LWP and N_{eff} in the satellite data allow us to examine S_R as a function of not only LWP, but also of N_{eff} . S_R varies as a function of N_{eff} , with maximum values where S_{POP} values are largest. Not surprisingly, the relative contribution of S_I increases as S_{POP} decreases with the increase in POP. Unfortunately, we are unable to adequately explain the negative values of S_I at low LWP, but can identify that the negative values occur in low LWP clouds with higher N_{eff} (Fig. 4). Given that the negative values of S_I run counter to our existing understanding of how precipitation responds to increases

in cloud droplet number concentrations and that they do not always occur in the regional susceptibilities, further inquiry into the CloudSat radar profiles of thin, polluted clouds is necessary to determine whether it is indeed a physical feature, controlled by factors such as turbulence or giant cloud condensation nuclei, or an artifact of our satellite retrievals.

Because LWP and N_{eff} distributions vary across different regions, we expect that susceptibilities to also vary by region. Indeed we find that this is the case, but even given the regional differences in susceptibilities, they still cannot explain the discrepancy between the S_{POP} values from *Wang et al.* [2012] and the values in this study and others [*Teraï et al.*, 2012; *Mann et al.*, 2014]. Although various regional differences exist, the notable difference between the two sets of studies is the use of AI, as opposed to N_{eff} . The use of AI requires retrievals of clear sky aerosol optical depth, whereas the N_{eff} retrievals require overcast clouds. Thus, the results of *Wang et al.* [2012] tend to preferentially select clouds with lower cloud cover than this study. Second of all, AI is a column integrative measure, whereas N_{eff} is a volume concentration retrieval based on cloud top r_{eff} of cloud drops. These differences may affect the susceptibility values in ways that are yet to be fully explored. Ideally, this issue can be reconciled using satellite field data that allow both AI and N_d estimates.

Because the regional susceptibilities vary, the susceptibility in one region may not inform us about the susceptibility in another region. Although we attempted to identify the minimum set of controls that control the value and behavior susceptibility by examining the response of susceptibility to N_{eff} , we found that knowing the range of the LWP and N_{eff} in each region cannot be used to explain regional differences. The implication of this result is that there are additional controls on susceptibility beyond LWP and N_d that

will need to be identified before we may arrive at an understanding that connects regional susceptibility estimates to global estimates. Identifying these additional controls may also shed light on the negative S_I values found for thin, polluted clouds. Until those controls are identified, susceptibility needs to be estimated at the regional level.

Likewise, the LES study of *Lebo and Feingold* [2014] finds that the relationship between the cloud lifetime effect and S_{POP} differs by cloud regime. In other words, increasing S_{POP} in one region leads to an increase in cloud LWP, while in another region it leads to a decrease in cloud LWP. The variety of values of S_{POP} and the response of clouds to S_{POP} across regions suggests that it is unlikely that global S_{POP} provides strong constraint on how clouds respond to aerosol perturbations in the real world, despite apparently doing so in the model world. Since the precipitation susceptibility is more easily quantified using observations compared to process rates, such as autoconversion and accretion, a deeper understanding of the processes controlling susceptibility and its effects on clouds is necessary.

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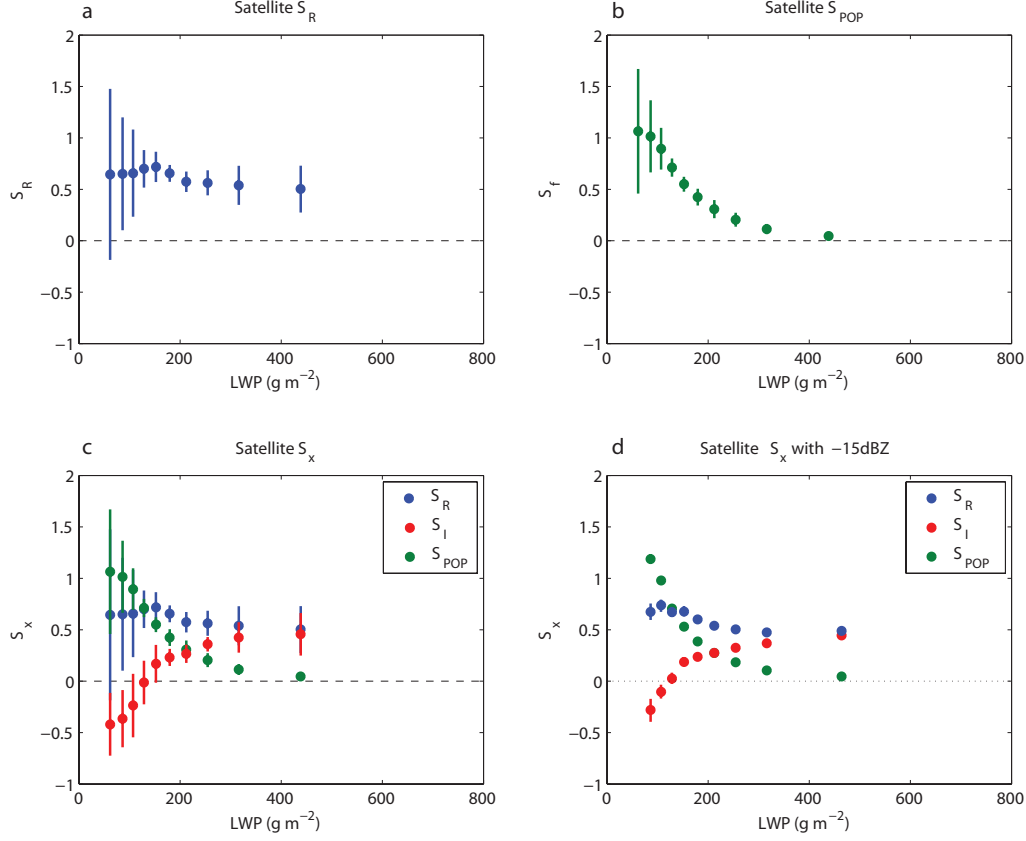


Figure 1. a) Susceptibility of mean precipitation rate (S_R) as a function of LWP, based on the satellite data and calculated using linear regression on N_{eff} -binned data. b) Susceptibility of probability of precipitation (S_{POP}) as a function of LWP, based on same data and method. c) S_R , S_{POP} , and susceptibility of precipitation intensity (S_I) as a function of LWP, based on same data and method. d) S_R , S_{POP} , and S_I , based on same data, but using the TLD method to calculate susceptibilities [Terai *et al.*, 2012].

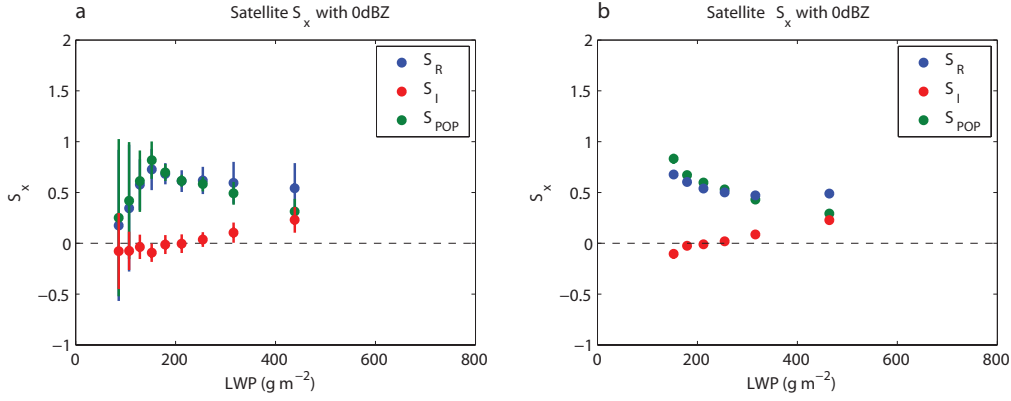


Figure 2. a) S_R , S_{POP} , and S_I as a function of LWP, as in Fig. 1c, but using a threshold of 0 dBZ to distinguish precipitating clouds. b) Same as a), but using the TLD method [Teraï *et al.*, 2012].

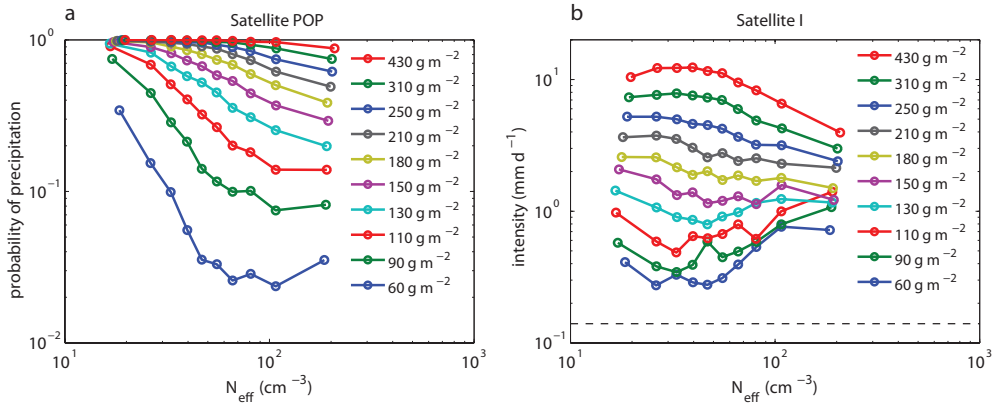


Figure 3. Probability of precipitation (POP) (a) and precipitation intensity (I) (b) as a function of effective cloud droplet number concentration (N_{eff}). Each line corresponds to the relationship in a particular LWP bin. The dashed line represents the precipitation equivalent of the -15 dBZ threshold used.

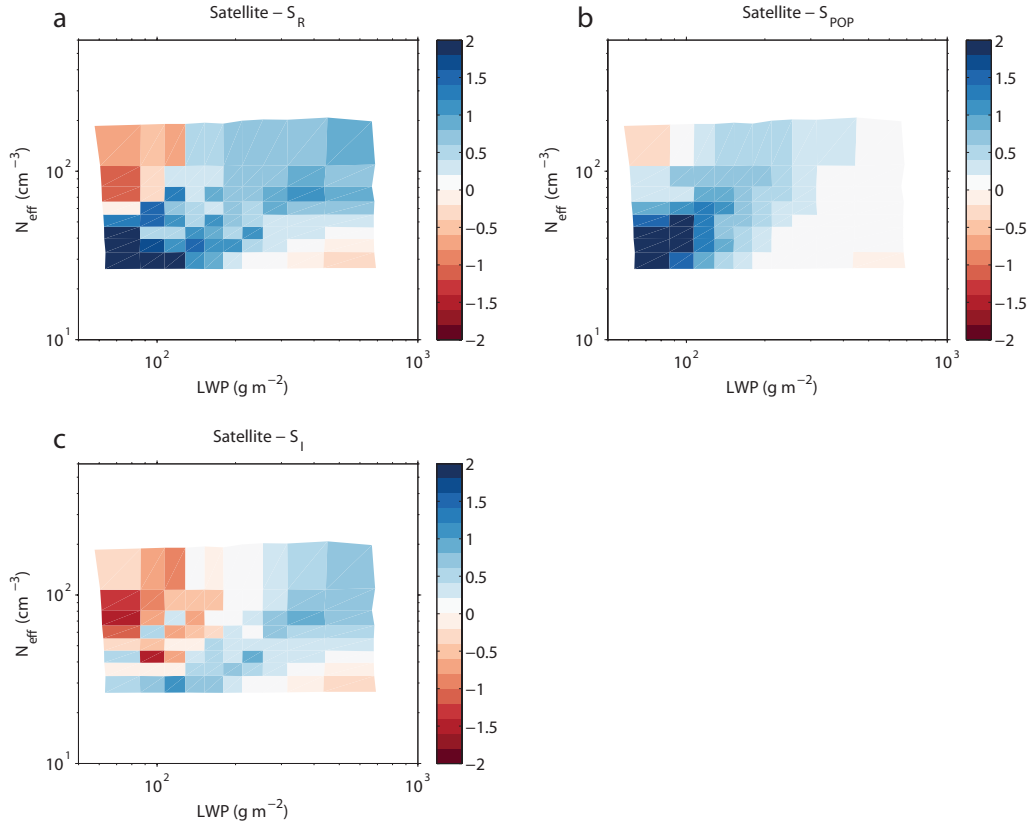


Figure 4. Susceptibility as a function of LWP and N_{eff} calculated from linear regression of three adjacent N_{eff} bins. S_R (a), S_{POP} (b), and S_I (c) from the satellite data.

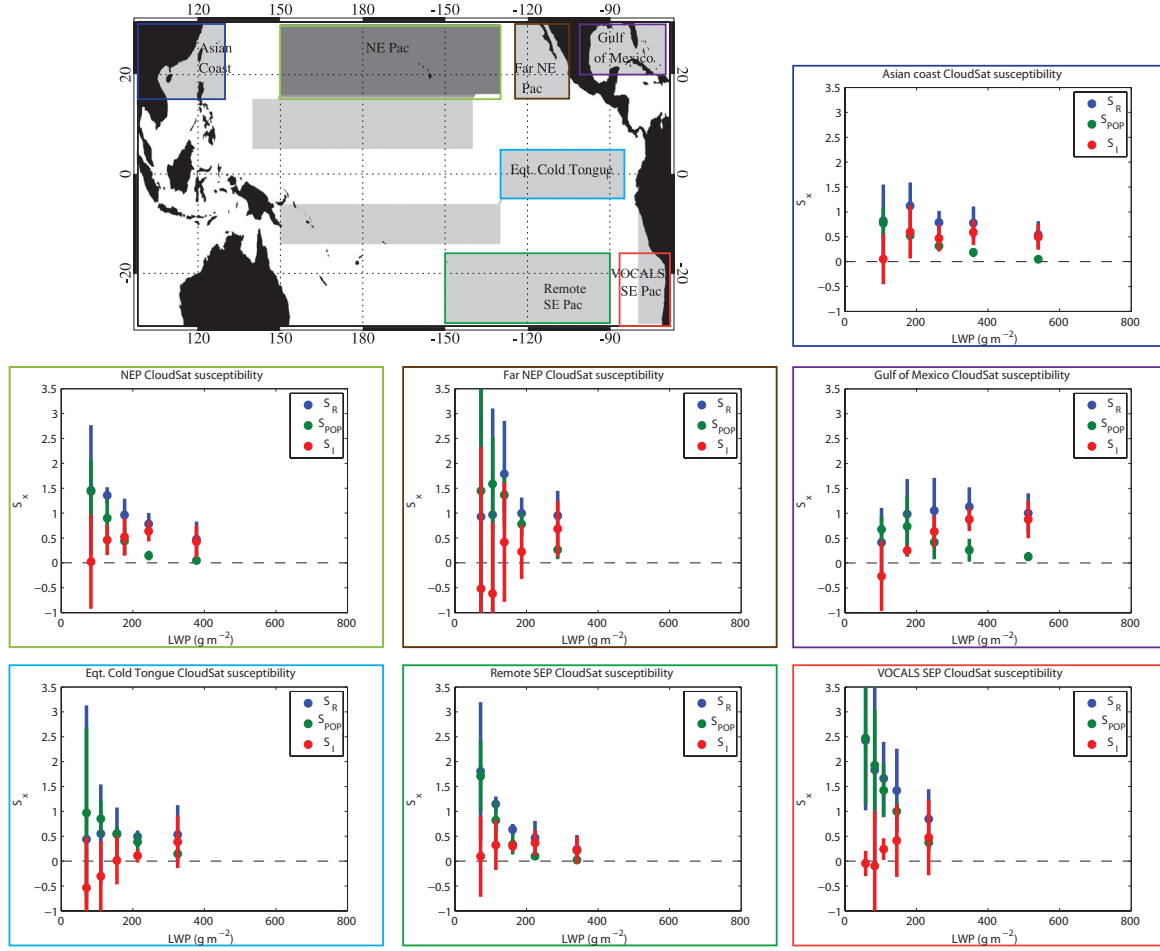


Figure 5. S_R , S_{POP} , and S_I as a function of LWP in seven different ocean basins: Asian coast, northeast Pacific, far northeast Pacific, Gulf of Mexico, equatorial cold tongue, VOCALS southeast Pacific, and remote southeast Pacific (adapted from *Kubar et al.* [2009] ©American Meteorological Society. Used with permission.).

Table 1. Mean LWP, effective cloud droplet number concentration (N_{eff}), and susceptibility values across different regions. The geographic extent of each region may be found in Fig. 5. Next to the regional-mean values of LWP and N_{eff} , the range (10th and 90th percentile values) are reported in brackets. After the regional mean susceptibility values, the susceptibility values estimated from applying the susceptibilities in Fig. 4 to the distribution of LWP and N_{eff} in each region are noted in brackets.

Region	LWP (g m^{-2})	N_{eff} (cm^{-3})	S_R	S_{POP}	S_I
Asian coast	290 [107,540]	199 [41, 444]	0.6 [0.6]	0.4 [0.3]	0.6 [0.3]
Equatorial Cold Tongue	175 [70,325]	69 [29, 127]	0.5 [0.7]	0.5 [0.7]	-0.1 [-0.0]
Far northeast Pacific (NEP)	158 [73,257]	83 [32, 163]	1.1 [0.5]	1.1 [0.5]	0.0 [-0.1]
Gulf of Mexico	277 [102, 512]	171 [30, 404]	0.9 [0.6]	0.9 [0.6]	0.5 [0.2]
NEP	202 [83, 378]	52 [20, 101]	1.6 [0.6]	1.0 [0.6]	0.4 [0.1]
Remote southeast Pacific (SEP)	183 [72, 341]	37 [17, 68]	0.9 [0.8]	0.6 [0.7]	0.3 [0.1]
VOCALS SEP	126 [58, 234]	73 [25, 151]	1.6 [0.6]	1.4 [0.8]	0.2 [-0.2]